



A multimedia framework for personalized, non-intrusive advertising in video streaming

Marco Furini¹

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Abstract

Traditional advertising is becoming increasingly ineffective as viewers actively avoid interruptions by engaging with second screens. Product placement has emerged as a popular alternative, with investments growing by 170% over the past decade. However, conventional product placement lacks interactivity and real-time personalization, which can limit its effectiveness. This study explores a multimedia framework designed to shift advertising in video streaming from intrusive interruptions to a user-activated model. The proposed approach links personalized advertising messages to video content, aiming to offer a lightweight, scalable, and user-centric product placement mechanism. Instead of disruptive commercials, on-demand messages appear through overlay boxes only when requested by the viewer. By connecting ads at playing time rather than filming time, the framework has the potential to keep product information relevant beyond the original release of the video. From a technical perspective, it operates on the client side via JavaScript, minimizing server load. To assess initial user attitudes, we conducted a proof of concept and administered a questionnaire to 104 young adults. Statistical and cluster analyses indicated that 56.7% of respondents preferred the proposed product placement approach over conventional ads, and 45.2% expressed willingness to use the tool, including some initially skeptical participants. While these findings highlight the potential of non-intrusive, user-driven advertising models to enhance engagement, they should be interpreted with caution due to the small, demographically narrow sample and reliance on self-reported data. Future research in real-world streaming contexts and with more diverse populations is needed to validate these preliminary trends.

Keywords Interactive product placement · Viewer engagement · Personalized advertising · Multimedia framework · Real-time purchase integration

1 Introduction

In today's digital media environments, viewers increasingly avoid traditional advertising formats [1]. When ad-skipping options are not available, viewer often engage in *second-screening* activities, such as using smartphones, tablets, or laptops. Empirical evidence shows that 54% of viewers chat with friends, while 58% engage in social media during these advertising breaks [2].

Product placement has emerged as a widely adopted alternative to traditional advertising, integrating recognizable products into video content to attract viewers' attention [3]. Over the past decade, investment in product placement has increased by 170% compared to traditional advertising. However, despite its growth, traditional product placement faces significant limitations [4].

A key limitation lies in the absence of an immediate connection between viewers and products. When encountering a product on screen, viewers must independently search for it online or offline to make the purchase, which undermines the possibility of impulse buying. Another limitation relates to the temporal relevance of product placement. Since products are placed at the time of filming, their relevance can decrease over time: a viewer watching the video years later may encounter brands or products that are obsolete or no longer attractive. Another limitation is the lack of personalization: the product is advertised by simply placing the product

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✉ Marco Furini
marco.furini@unimore.it

¹ Department of Communication and Economics, University of Modena and Reggio Emilia, Viale Allegri 9, 42121 Reggio Emilia, Italy

in the video. While personalization alone does not guarantee advertising success [5], several studies have shown that personalized advertising can enhance user engagement and perceived relevance [6, 7], making it a highly valued strategy for advertisers [8]. Finally, it is worth highlighting that excessive use of this strategy can reduce viewers' engagement with the featured product or brand [9, 10].

To overcome these limitations, this study addresses a key research question: *Can multimedia technology connect products to video scenes and support personalized, non-intrusive advertising to influence user attitudes and engagement?*

We propose a multimedia framework that aims to transform product placement in streaming content by enabling non-intrusive, user-initiated interactions for instant access to product information. Our solution links products featured in scenes or mentioned in dialogues directly to video content, by linking products to the exact moment they appear or are mentioned, thereby targeting points of heightened user attention of interest (e.g., tasting a new food or purchasing a smartphone). Since this impulse is often fleeting and rarely translates into concrete action, our framework leverages this time window by offering immediate access to information through direct interaction with the video player. This approach is designed to satisfy the viewer curiosity while potentially creating new engagement opportunities for brands.

Unlike advertising and traditional product placement strategies, our framework follows a 'pull' rather than 'push' model: product details appear only when the user initiates an interaction, such as hovering over or tapping the screen. This preserves focus on the video content while ensuring a non-intrusive advertising experience. Furthermore, ad personalization relies solely on data provided by users during streaming platform registration, ensuring compliance with privacy regulations such as GDPR. The goal is to deliver advertising that is timely, relevant, unobtrusive, and personalized.

From a technical standpoint, the framework avoids resource-intensive solutions like 2D or 3D graphics and instead employs a lightweight client-based architecture with JavaScript event listeners. This minimizes server load and ensures scalability and real-time responsiveness.

To assess user attitudes toward interactive product placement, we developed a proof-of-concept and conducted a study with 104 young adult volunteers. The prototype demonstrated the feasibility of our approach using simple technologies, such as JavaScript event listeners to trigger overlay messages and JSON to associate information with video content. After showing the tool, participants completed a questionnaire evaluating their streaming habits, opinions on product placement, past behaviors, and interest

in our solution. Following verification of the questionnaire's robustness and internal consistency (Cronbach's alpha = 0.78), we conducted statistical analyses and a cluster analysis. The results suggested that: 75% of the participants preferred streaming platforms over traditional television, 56% favored product placement over conventional advertisements, and 45% expressed willingness to use our tool. In particular, only 12% found product placement strategies annoying and 24% enjoyed searching for products seen on the screen.

The cluster analysis identified distinct user profiles, while correlation analysis showed that users previously influenced by product placement were more likely to interact with our tool. Notably, even initially skeptical participants displayed a certain level of interest in our approach.

These preliminary findings, together with existing evidence on audience resistance to interruptive advertising formats and emerging interest in interactive, user-driven product placement strategies, highlight the relevance of further exploring innovative models for advertising integration in digital media.

The remainder of the paper is organized as follows. Section 2 presents recent studies that seek alternatives to classic commercial breaks. Section 3 shows the details of our proposal. A proof of concept is presented in Sect. 4. Section 5 presents an experimental evaluation study. A discussion of the results obtained is presented in Sect. 6. Conclusions are drawn in Sect. 7.

2 Related work

This section reviews existing research on key areas relevant to our study, including technological solutions for product placement in video content, personalized advertising strategies, viewer engagement through interactive elements, and the theoretical foundations underlying advertising effectiveness.

2.1 Technological solutions for viewing-time product placement

In traditional product placement, products are embedded in video content during production. However, since films and TV series are often viewed years after their release, this advertising model has a major limitation: the relevance of the featured products diminishes over time.

To address this issue, Hudson and Hudson [11] proposed using interactive elements and augmented reality. Their approach provided additional product information on screen during playback, enhancing relevance but without allowing viewer interaction. Bhargavi et al. [12] introduced a similar

concept by digitally inserting products into TV and movie scenes, focusing on 2D ad placements in cooking shows. Their goal was to seamlessly integrate product imagery into contextually relevant scenes while preserving the viewing experience. Fong and See [13] leveraged pre-trained Stable Diffusion models to generate images based on simple text prompts, allowing rapid prototyping and concept creation. However, their approach requires significant computational resources, making it impractical for current use. Allan et al. [14] used computer graphics to tailor the broadcasts to individual viewers. Their framework, designed for football and rugby games, employed AI models to detect players and the ball, overlaying media objects in suitable areas of the screen. Foss et al. [15] explored personalized product placement by using user profile data. Their approach, based on the MPEG-4 and MPEG-7 standards, dynamically inserts customized objects into video playback. However, the need to re-encode video material for each viewer makes this method more theoretical than practical. Li et al. [16] investigated user-controlled experiences in a Web context. Their study, although focused on 3D ads, highlighted the importance of engaging experiences that enhance product knowledge, brand attitude, and purchase intention.

Although these studies present innovative solutions, many require substantial computational power, posing challenges for resource-constrained environments like video streaming platforms. Devices such as TV sticks often lack the capacity to handle such resource-intensive processes. In contrast, our approach ensures long-term relevance without demanding high computational resources, making it highly suitable for low-capacity devices while effectively addressing the shortcomings of traditional product placement.

2.2 Personalized advertising

Personalization plays a crucial role in enhancing user engagement and improving advertising outcomes by tailoring content to individual preferences. This approach not only fosters a more pleasant user experience, but also significantly influences purchasing decisions [17, 18]. In today's digital landscape, where data-driven algorithms dominate content delivery, personalized advertising has emerged as a powerful tool to improve marketing effectiveness [15, 19]. The rationale behind these strategies lies in the understanding that consumers are more likely to respond positively to content that aligns with their unique interests, preferences, and purchasing behaviors [20].

In this area, different approaches emerged. Content-based personalization leverages a user's past preferences and consumption habits to recommend products or advertisements. This method is particularly effective on media platforms, where aligning content with user preferences improves

engagement [21]. Tucker [22] demonstrated that personalized ads, tailored based on user-generated social media content, can significantly enhance engagement. However, Tucker also highlights that excessive personalization without proper transparency may provoke resistance, ultimately diminishing ad effectiveness. Context-aware personalization uses real-time contextual factors such as location, time, or device type to deliver timely and relevant ads. Studies have shown that aligning the content of the ads with the user's immediate environment improves engagements [23]. For example, Furini [7] used location-based information to produce personalized overlay ads, demonstrating their superior effectiveness in capturing attention and driving engagement on advertising-based video-on-demand platforms. Behavioral Targeting relies on user behavior data such as browsing patterns, clicks, and purchase history to tailor advertisements. This method has been shown to increase click-through rates while improving customer satisfaction [24]. Bleier and Eisenbeiss [24] demonstrated that the use of consumer behavior data, such as clickstream data from an online retailer, effectively increases ad performance and consumer engagement.

In our study, we do not propose a new personalization algorithm, nor do we focus on testing the effectiveness of existing personalization approaches. Instead, our goal is to design a framework that provides advertising agencies with the necessary data (e.g., user information, contextual data, product details, and content insights) to support the implementation of the personalization strategy deemed most suitable for a given user and situation.

2.3 Video interaction and viewer engagement

The ultimate goal of advertising and product placement is to engage viewers, promote product interest, and enhance brand memorability [4]. Achieving this goal requires strategic product visibility and contextual relevance to sustain viewer engagement without disrupting their experience. Research highlights the importance of aligning product placement with the narrative context. Russell [25] emphasized that the congruence between the product and the storyline is crucial. When a product appears out of place or feels forced into a scene, viewers may develop negative perceptions, reducing their purchase intent. Conversely, seamless product integration enhances positive consumer responses and reinforces brand recall. Cowley and Barron [26] further demonstrated that viewers often struggle to remember products placed in films, especially when these products are not meaningfully connected to the plot. This finding underscores the need for placements that blend naturally into the viewing experience to enhance memorability and engagement. Law and Braun [27] explored how viewers subconsciously

develop preferences for brands encountered through subtle, well-integrated placements. Their findings align with the principles of "pull" advertising. Unlike traditional "push" advertising, which interrupts viewers with forced promotional content, "pull" advertising relies on creating curiosity and prompting voluntary engagement. In this approach, viewers actively seek product information because it is presented in a relevant, subtle, and non-intrusive manner. For example, instead of a disruptive pop-up ad, the product appears naturally within the video scene, prompting viewers to explore it at their own discretion. This method encourages self-directed discovery, giving viewers greater control over their engagement with promotional content.

Our proposed framework builds on this "pull" strategy by integrating product information non-intrusively into video content. Viewers can access product details only when they choose to interact (e.g., by hovering over the screen or tapping a designated area). By aligning with user curiosity rather than forcing content, our approach reduces ad fatigue while fostering engagement.

2.4 Theoretical foundations of advertising and engagement

Successful advertising strategies rely not only on advanced technological solutions but also on well-established psychological and communication theories that explain how users perceive, process, and respond to marketing content. For instance, Blumler and Katz [28] argue that media consumers actively select content that satisfies specific needs, such as obtaining information, seeking entertainment, or engaging in social interaction. Additionally, Petty and Cacioppo's *Elaboration Likelihood Model* [29] identifies two main routes through which individuals process persuasive messages: the central route (which involves thoughtful and deliberate consideration of the presented information); the peripheral route, where individuals rely on superficial cues such as visual appeal or brand recognition. Finally, Davenport and Beck's attention theory [30] emphasizes that content must be designed to efficiently capture and sustain user attention.

Building on these theoretical foundations, our proposed framework integrates key psychological principles to enhance viewer engagement, cognitive processing, and attention management. Specifically, our system encourages users to voluntarily interact with product placement content in alignment with their individual preferences and information-seeking behaviors [28]. By giving users greater control over product discovery during video consumption, the framework leverages user autonomy to foster deeper engagement. At the same time, it accommodates both highly motivated users and less engaged users. The former

can explore detailed product information via interactive elements, the latter may unconsciously develop positive brand associations through passive exposure [29]. Lastly, our framework delivers product information in a non-intrusive manner, allowing viewers to display ads during natural video pauses or non-critical narrative moments [30].

3 Research design

To address the research question posed in this paper (*Can multimedia technology connect products to video scenes and support personalized, non-intrusive advertising to influence user attitudes and engagement?*), we propose a multimedia-driven framework designed to integrate video content and personalized advertising messages in a user-initiated, non-intrusive way. Our approach is guided by the following key principles:

- *From Push to Pull*: Product information appears on-screen only when viewers actively interact with the video player (e.g., hovering or tapping the screen). This is intended to support a non-intrusive yet engaging experience.
- *Scalable*: To minimize client/server load and computational demands, our framework avoids the use of resource-intensive technologies like 3D or AR computer graphics.
- *Immediate*: The system aims to facilitate immediate access to products at moments of interest, potentially supporting impulse-driven behaviors.
- *Personalized*: Ad messages are dynamically tailored to both the video scene and the individual viewer, enhancing relevance and engagement.
- *Dynamic*: Messages are synchronized with playback time rather than production time, which is designed to keep product information up to date even when viewers access the content long after its original release.

To implement these principles, we propose the following architecture.

3.1 The framework architecture

Fig. 1 illustrates the architecture of a typical video streaming platform. The modules we introduced to enable seamless, non-intrusive, and personalized ad messages are highlighted in blue.

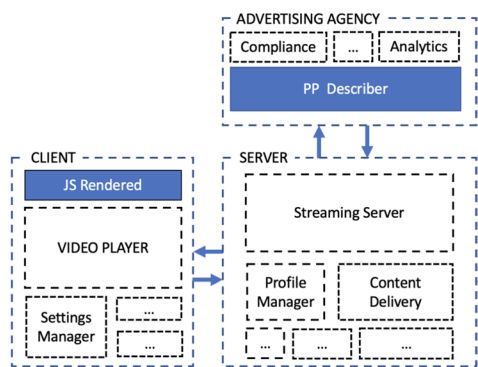


Fig. 1 A typical video streaming architecture. Blue boxes indicate the modules introduced to provide seamless, non-intrusive, and personalized advertising messages

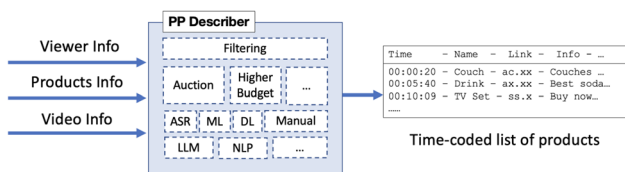


Fig. 2 The “PP Descriptor” module transforms viewer and product data into a time-coded list of product placements using various selection policies

3.1.1 Advertising agency

The advertising agency acts as an intermediary between companies that want to advertise their products and the streaming platform that provides video content to viewers. Our goal is to exploit the so-called *desire induction* or *impulse activation*, a mental process where seeing an item triggers the desire to purchase or possess it [31, 32]. This phenomenon is related to the reward system of the brain, where visual stimuli release dopamine, creating a sense of anticipation and satisfaction [33].

Since the appearance or mention of a product in a video can evoke such a connection, our approach aims to harness impulse-driven consumer behavior effectively. Given that a video comprises a sequence of scenes, each scene potentially contains products eligible for promotion. Therefore, the advertising agency might associate ad messages with each specific video scenes. This association is described through a time-coded list specifying when and which messages should be displayed, along with relevant details such as product descriptions, prices, and purchase links. The PP Descriptor is in charge of generating this list. Figure 2 shows its functionality: It takes as input viewer data (if available), product information, and video details, and outputs a personalized time-coded list of ad messages.

- *Viewer info.* This data is provided by the streaming platform (e.g., Netflix and Disney+), typically collected

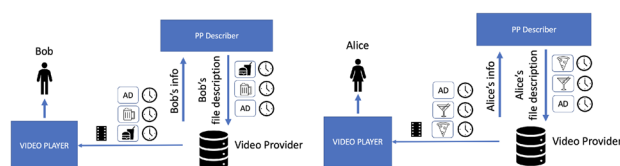


Fig. 3 Example of personalization. Different products are advertised for the same video. If Bob (left side) interacts with the video player, he will see ads different from the ones Alice (right side) will see

during the registration process. Viewers are usually characterized by basic attributes (e.g., age, gender) and device-specific information, such as geographic location and session time. By relying solely on data collected by the video streaming platform, our approach mitigates potential privacy concerns and aligns with privacy regulations.

- *Products Info.* This data is supplied by advertisers when they establish contracts with the advertising agency. Similarly to web advertising practices, product data include targeting criteria (e.g. suitable age, gender, location), budget parameters (e.g., per-play bid limits, overall budget), and keywords to identify the most relevant scenes for placement.
- *Video Info.* This data is provided by the streaming platform or video distributor and describes each video scene with a set of keywords that semantically characterize it. This description is strongly tied to the video and can typically be generated once for all scenes. If unavailable, the advertising agency can create this description using technologies such as ASR (Automatic Speech Recognition), ML (Machine Learning), DL (Deep Learning), LLM (Large Language Models) or manual annotation.

Using the above data, the PP Descriptor module produces a time-coded list of personalized ad messages, with each message linked to a specific time range within the video. This list precisely determines when each message appears, allowing seamless and dynamic insertion of ads during playback. For example, when a viewer watches a rerun of Friends, personalized ad messages align with playback time, making the content more relevant and engaging for today’s viewers. When multiple products qualify for a single scene, the PP Descriptor applies a selection policy (e.g., auction, highest bid, advertiser budget) to filter the products. Since these policies are business-driven, they fall outside the scope of this paper. Therefore, in our study we assume a predefined policy selects a single ad message when multiple options are viable. Figure 3 shows an example with two viewers watching the same video: Bob sees a hamburger ad, while Alice sees a pizza ad.

The PP Descriptor module can be formalized as follows:

Definition. Let N be the number of scenes in the video, let M be the number of available advertising messages, and let K be the number of viewers.

Viewer Description. Each viewer U_i (where $i = 1, 2, \dots, K$) can be described by a tuple: $U_i = (age_i, gender_i, location_i)$ where age_i , $gender_i$, and $location_i$ denote the age, the genre, and the location of the viewer i , respectively.

Video Description. A video V is represented as a set of N scenes: $V = \{S_1, S_2, \dots, S_N\}$, where each scene S_i is described by $S_i = (start_i, end_i, keywords_i)$. Table 1 shows an example of a video description. As mentioned above, this description is provided by the streaming platform or the content distributor. Otherwise, it can be produced by the advertising agency through technologies or human beings.

Product Description. Each ad message P_j (where $j = 1, 2, \dots, M$) can be represented by a tuple containing various attributes: $P_j = (name_j, link_j, info_j, advertiser_j, budget_j, bid_j)$ where $name$ is the name of the product, $link$ provides a link to more information or purchase options, $info$ includes additional details about the product, $advertiser$ is the advertiser associated with the product, $budget$ is the advertiser’s total budget for this product placement, bid is the bid value for placing the product within a scene, $keywords$ is the set of keywords that describe the product, $age - group$ is the age of the target audience, $gender$ is the gender of the target audience. Table 2 shows an example of the product description. As mentioned above, these data are provided by advertisers when signing up with the advertiser agency.

Product Placement Selection Policy. Given a viewer U_k , a video scene S_i , a list of products P_1, P_2, \dots, P_M , the PP Descriptor can be seen as a function f able to find the right product for the specific viewer k .

$$f : S_i \times U_k \times \{P_1, P_2, \dots, P_M\} \rightarrow (S_i, P_j) \quad (1)$$

As mentioned, the function filters the available products based on video description and on viewer’s profile. Since the filtering process might use business-driven policies that fall outside the scope of this paper, in this study, we assume a predefined policy selects a single ad message when multiple options are viable.

Table 1 Video description: each scene is described through a time range and a set of keywords

Time	Keywords
00:00:10–00:00:11	New York background
00:00:12 - 00:01:53	Living room, Friends, Wine, band, musical, candy
00:01:54 - 00:02:28	Shoes, diamond, bed, wedding, bride
00:02:28–00:02:31	New York background
00:02:32–00:03:01	Living room, suite, tie
00:03:02–00:05:00	Videogame, basketball, TV, chair, jeans, hat, playstation

3.1.2 Server

The server, managed by the video streaming platform, serves as the central hub for content distribution and coordination with the advertising agency. It processes client requests, retrieves relevant multimedia content, and communicates with the ad agency to obtain a time-coded list of product placements for each video.

Unlike various approaches in the literature that rely on computationally intensive 2D, 3D, or AR rendering to personalize advertising messages (e.g., [12, 15]), our framework minimizes the server’s computational workload. Instead of handling resource-heavy rendering, the server performs only lightweight tasks: transmitting available viewer data to the advertising agency, receiving a time-coded list of personalized ad messages, and forwarding this list to the client. This design significantly reduces server-side processing while still enabling dynamic and personalized advertising.

3.1.3 Client

The client-side video player does not require a full redesign, as JavaScript is sufficient to dynamically display messages over the video. When a viewer asks for a video, the client sends a request to the server, which responds with the video and a time-coded list of associated products. This list is processed by the JS Renderer (see Fig. 1), a simple JavaScript script that manages viewer interactions.

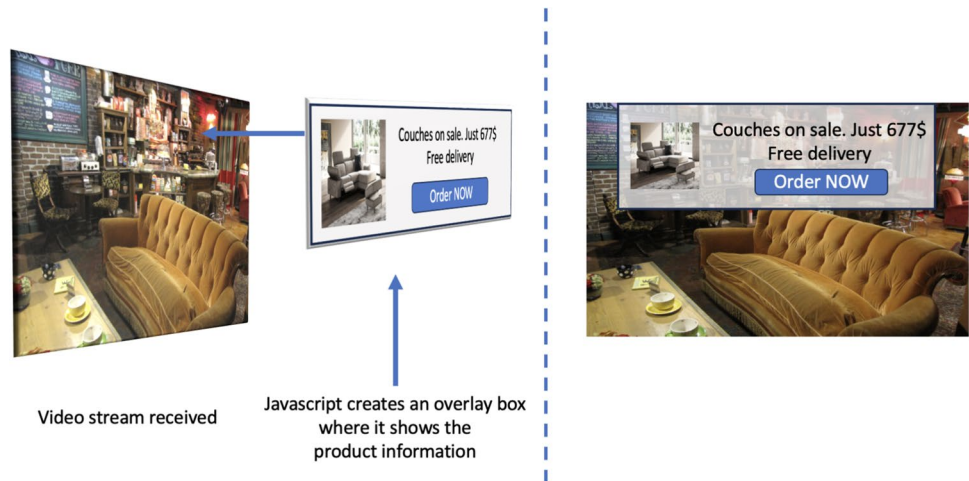
The video player begins playing and displays personalized ads in an overlay box upon viewer interaction. Figure 4 shows the process. When a viewer interacts with the video player (e.g. by hovering over it), the JS Renderer

Table 2 Product description: each product is described through a set of features

Name	Keywords	Age	Gender	Bid	Info	Other
Candy Pro	Candy	any	any	5	Buy online..	...
Couch	Living room, friends	30–40	F	3	Looking for..	...
Musical	Music, friends	30–40	M	4	Ticket now..	...
Wedding ring	Wedding, ring, bride	20–40	F	6	Diamonds are..	...
Sport Jersey	Soccer, basketball	15–25	M	4	Famous jersey..	...

(Gender: F Female, M Male)

Fig. 4 At the client side, a JS script creates an overlay box with the personalized ad message (left). When the viewer interacts with the video player (e.g., mouse-over or touch), the overlay box is shown (right)



dynamically displays an overlay box with a personalized message. Without interaction, no overlay box is shown.

This approach ensures minimal computational load on the client side, making it compatible with low-power devices such as streaming sticks. Moreover, it delivers personalized ad messages in a non-intrusive manner, as the overlay box appears only when the viewer actively engages, preserving content integrity and enhancing the viewing experience.

4 Proof-of-concept

To illustrate the feasibility of our proposal and provide a basis for experimental testing, we developed a proof of concept featuring a scenario inspired by real-world advertising dynamics, in which potential advertising messages are linked to a video and displayed to end users upon interaction with the video player. The goal is to explore how such a system could support a more active, personalized, and engaging viewing experience.

To set up the proof of concept, we defined three hypothetical user profiles, Alice (32), Bob (54) and Frank (19), to illustrate how personalization rules could be applied to different demographic segments. For the video content, we manually generated scene descriptions for a 5-minute segment from an episode of Friends. Table 1 shows the six distinct scenes, while Table 2 shows a hypothetical list of products, including features such as keywords, demographics of the target audience, and bid amounts for ad placement. Additional features, such as video gender, rating, or air time, could also be incorporated to refine the targeting.

In a real-world scenario, viewer data would be provided by the video streaming platform, while product features would be supplied by advertisers, as is currently the case in web advertising [34]. Video descriptions could alternatively be supplied by the advertising agency or video producer using automated recognition technologies. Although

video description methodologies are outside the scope of this paper, it is important to note that streaming platforms frequently associate videos with high-level, time-coded semantic descriptions. For example, Amazon Prime enriches video scenes with structured metadata in JSON format: when viewers interact with video players, information about actors, characters, and background music is displayed on-screen [35].

4.1 Advertising agency

The advertising agency processes video descriptions, viewer data, and product information to generate a time-coded list of personalized ad messages. Without loss of generality, we assume that the agency employs a simple bid-based selection policy. Consequently, the time-coded list for Alice includes Candy Pro in scene #2, Wedding Ring in scene #3 and Couch in scene #5. The list for Bob includes Candy Pro in Scene #2, while the list for Frank includes Candy Pro in Scene #2 and Sport Jersey in Scene #6.

4.2 Server

The server receives viewer requests, along with viewer and video data, sends this information to the advertising agency, and retrieves the time-coded list of messages. Finally, it forwards the list to the client.

4.3 Client

At the client-side, we use a few JavaScript event listeners to trigger the overlay dynamically based on viewer's interaction. Figure 5 shows how the same viewer might experience the same video scene of actors talking about candies. If a user does not interact with the video player, no additional content is shown on screen (Fig. 5-left). If he/she hovers the

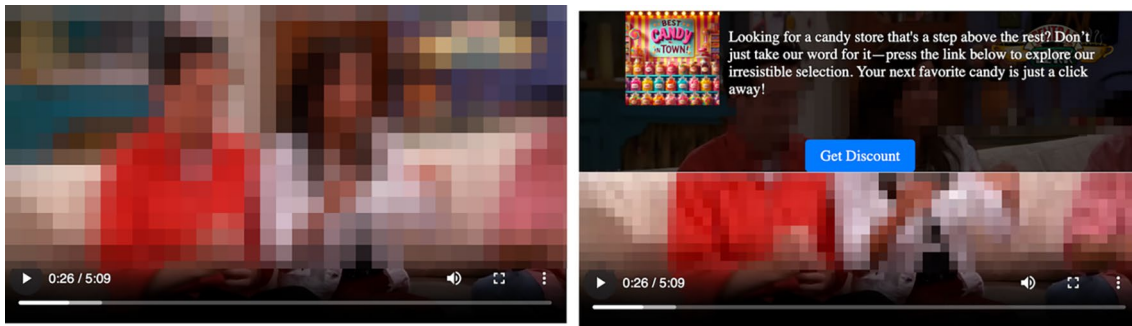


Fig. 5 Viewer's experience when watching a video scene where actors are talking about candies: no interaction (left); hovers the mouse on the video player (right). Images are pixelated for copyright reasons

mouse over the video player, an overlay box with personalized information appears (Fig. 5-right).

4.4 Implementation challenges

While our proof-of-concept successfully demonstrates the feasibility of our proposed framework, deploying such a system in real-world environments introduces additional complexities that require careful consideration.

- **Synchronization Accuracy.** Precise timing is crucial to ensure that overlay advertisements appear at appropriate moments in the video. Misalignment of even a few seconds could confuse viewers or reduce the perceived relevance of the displayed product. To address this, synchronization can be improved using timestamps extracted from the video's metadata (e.g., SMPTE timecodes, or scene-based semantic markers). These markers provide stable reference points to align ad triggers with relevant video moments.
- **Ad Relevance Algorithms.** Ensuring contextual coherence between video content and advertised products is a fundamental requirement for enhancing engagement and minimizing frustration. A lack of relevance can undermine user trust and reduce the effectiveness of campaigns, regardless of the delivery method. This requirement applies to all forms of advertising and is not a limitation specific to our framework. Our focus is on the technological infrastructure, not on the editorial or commercial decisions regarding which products are promoted in which scenes. The responsibility for ensuring ad relevance lies entirely with the advertising agency, which may adopt manual curation strategies or employ AI-based approaches to select appropriate ads based on video content and audience profiles. As with traditional advertising, the success of these strategies depends on the quality of execution, not on the delivery framework itself.

- **Latency and Performance.** Interactive overlays must appear promptly to ensure a smooth viewing experience. Latency issues could frustrate users and reduce engagement. The proof-of-concept shows that lightweight JavaScript event listeners are sufficient to avoid latency and performance problems. However, further optimizations, such as preloading ad content, client-side caching, and asynchronous data retrieval, might be used to improve responsiveness.

5 Experimental assessment

The experimental analysis aims to assess viewers' attitudes toward product placement strategies and their willingness to interact with the proposed framework to access information about displayed products. In the following, we present details on the questionnaire and the participants involved in the evaluation. The analysis begins with a reliability check using Cronbach's alpha, followed by descriptive statistics and a cluster analysis to identify potential participant groups with similar characteristics and understand their behavior.

5.1 Questionnaire

The questionnaire was designed to investigate key factors influencing the adoption and perceived value of the proposed framework. To comprehensively capture both user attitudes and behavioral tendencies, a 5-point Likert scale was employed to examine four thematic areas:

- **Viewing habits on streaming platforms** (e.g., frequent use of platforms, preference for streaming over traditional TV, usefulness of interactive features, satisfaction with content quality, desire for more interactivity). This section investigated users' digital consumption habits, as frequent streaming usage and interest in interactive features may influence engagement levels [36].

- Attitudes toward product placement (e.g., awareness of product placement, perception of annoyance, influence on brand perception, preference over traditional advertising, impact on perceived content quality). This section explored user perceptions and acceptance levels toward product placement to determine whether our interactive product placement is perceived as intrusive or, conversely, as useful.
- Past behaviors related to product placement (e.g., online searches, purchases influenced by viewing products in video content). This section examined whether viewers have previously engaged in such behaviors, including searching for products online or making purchases after seeing them in video content.
- Interest in a product placement tool (e.g., perceived usefulness, willingness to use, interest in store location and price comparison). This section assessed users' interest in the proposed framework and their preferences regarding its core features.

5.2 Participants

Young adults (18–26) are widely recognized for their significant role in shaping digital trends and consumer behavior. This age group not only actively consumes digital content but also responds rapidly to innovations, often acting as social amplifiers who influence trends and purchasing decisions [37]. Their role as trendsetters makes them a strategic marketing target, particularly given their strong propensity for online shopping and their influence on broader consumer behaviors [38, 39]. Moreover, young adults have shown a notable openness to innovative advertising approaches, such as interactive product placement, making them particularly receptive to changes in perception and behavior in response to such stimuli [40]. This characteristic aligns closely with the objectives of our study, leading us to specifically recruit participants from this age group.

A total of 104 young adults participated in our study by completing the questionnaire, a sample size consistent with previous research in the field of personalized advertising [41–44]. Given their digital engagement and openness to innovation, this demographic provides a valuable testing ground for assessing the tool's impact on user adoption and purchasing behavior. The insights gained can help define marketing strategies and serve as a foundation for future research.

5.3 Scale reliability and measurement considerations

Cronbach's α was computed to assess the questionnaire consistency. The overall α was satisfactory (0.78),

indicating good internal consistency across the full set of Likert-scale items. However, not all item groupings in this study were intended to represent reflective, unidimensional scales. Cronbach's α assumes that items are interchangeable indicators of a single latent construct and are expected to covary; when these assumptions are violated, low α values are expected and should not be interpreted as poor measurement quality [45].

The first two item groups, *Viewing habits on streaming platforms* ($\alpha = 0.27$) and *Attitude towards on-screen products* ($\alpha = 0.56$), were intentionally designed as multidimensional and descriptive indicator sets. The former captures different facets of media consumption, while the latter includes distinct evaluative dimensions (e.g., awareness, annoyance, perceived influence, and preference over traditional advertising). These indicators represent complementary aspects rather than interchangeable reflections of a single latent construct and are therefore closer to formative or composite constructs, for which internal consistency is neither theoretically required nor methodologically appropriate [46].

The individual items were used directly in the clustering analyses, which do not rely on internal consistency and benefit from multidimensional inputs. Similar approaches are common in exploratory research, where lower alpha values are considered acceptable for heterogeneous constructs [47].

By contrast, the remaining item groups, *Past attitudes towards product placement* ($\alpha = 0.71$) and *Interest in the proposed tool* ($\alpha = 0.77$), correspond to more homogeneous attitudinal constructs and show acceptable internal consistency. Overall, these results indicate that the questionnaire is appropriate for the exploratory aims of this study, while future confirmatory research may further refine these measures where unidimensional scales are theoretically justified.

5.4 Cluster analysis

The rationale for applying clustering analysis is to gain insights into how users differ in their receptiveness to interactive product placement. By identifying distinct segments with shared attitudes and behaviors, it becomes possible to explore how personalized advertising strategies might be developed in the future. For example, in a potential future application, a streaming platform could incorporate a brief questionnaire during the registration process to classify users into one of the clusters identified in this study. Such profiling could, in principle, support more tailored advertising experiences by offering interactive placements to segments more likely to engage, adapting content for more reluctant users, or providing targeted incentives to encourage participation.

Table 3 Descriptive statistics for viewing habits on streaming platforms

Variable	Mean	Std. Dev.	% positive (≥ 4)	95%	95%
				CI lower	CI upper
Streaming platform usage	3.99	1.23	67.3	3.75	4.23
Streaming better than TV	4.13	0.97	75	3.95	4.32
Usefulness of interactive features	3.65	1.03	54.8	3.45	3.85
Streaming platform satisfaction	3.80	0.91	68.3	3.62	3.97
Desire for more interactive features	3.14	1.19	38.5	2.91	3.37

From the advertisers' perspective, insights into the prevalence and characteristics of these clusters could inform more efficient budget allocation and campaign planning, by helping to prioritize receptive audiences with appropriate messaging formats.

To perform the clustering, we employed the K-Means algorithm, a widely used and effective technique for partitioning quantitative data such as Likert-scale responses. The optimal number of clusters was determined using both the Elbow method and the Silhouette score.

To validate this methodological choice, we also conducted a comparison with Hierarchical Clustering. The results showed a high degree of similarity in group structure and characteristics, supporting the robustness of the segmentation achieved through K-Means. Given its greater computational efficiency, only the K-Means results are reported in the following.

5.5 Viewing habits on streaming platforms

This section analyzes the set of questions on viewing habits in streaming platforms using descriptive statistics and applies cluster analysis to identify high-level patterns in user behavior.

The results reported in Table 3 indicate a strong preference for streaming services among respondents: *Preference for streaming over traditional television* has a **4.13** mean score with a substantial **75%** of positive responses. The variable *Usefulness of interactive features* obtained a moderate mean score (**3.65**) and a **54.8%** positive response rate, indicating divided opinions regarding the utility of interactive features. The results also indicate relatively low level of expressed demand for additional interactive functionalities: *Desire for more interactive features* has a **3.14** mean score, with only **38.5%** of respondents expressing positive feedback. The confidence intervals are relatively narrow for all variables, indicating the precision and reliability of the estimated means.

Table 4 Mean and standard deviation for each variable by cluster (scale 1–5)

Variable	Cluster 0	Cluster 1	Cluster 2
Streaming usage	3.00 \pm 1.06	4.65 \pm 0.72	3.86 \pm 1.36
Streaming better than TV	4.67 \pm 0.56	4.56 \pm 0.67	3.30 \pm 0.91
Usefulness of interactive features	2.96 \pm 0.69	4.19 \pm 0.91	3.49 \pm 1.04
Streaming platform satisfaction	3.08 \pm 0.72	4.42 \pm 0.59	3.54 \pm 0.87
Desire for more interactive features	2.21 \pm 0.8	2.91 \pm 1.06	4.03 \pm 0.87

The cluster analysis produced three distinct clusters, and ANOVA results support the presence of meaningful differences the clusters (see, Table 4 for mean and standard deviation). In particular, it revealed statistically significant differences across all five investigated dimensions. The most pronounced differences were found in *Streaming better than TV* and *Streaming platform satisfaction*, with F-statistics of 36.7 and 29.5, respectively, suggesting that these variables play an important role in distinguishing user groups.

Based on responses to the five questions, we label each cluster as follows:

- *Streaming Moderate* (Cluster 0: 24 users). Users characterized by low engagement and limited interest in interactive features. They report relatively low streaming usage and platform satisfaction, low perceived usefulness of interactive features, and the weakest interest in additional interactivity. While they still express a preference for streaming over traditional TV, their overall profile suggests a more conservative and less innovation-oriented viewing behavior.
- *Streaming Enthusiasts* (Cluster 1: 43 users). Users showing high usage, satisfaction, and appreciation of platform features. They report the highest levels of engagement with streaming platforms, very frequent streaming usage, high platform satisfaction, and strong perceived usefulness of interactive features. Although their desire for additional interactivity is moderate, they display a clear preference for streaming over traditional TV and a generally positive attitude toward platform features.
- *Streaming Explorers* (Cluster 2: 37 users). Users characterized by strong interest in additional interactivity despite moderate usage levels. They show moderate-to-high streaming usage and moderate satisfaction, together with a weaker preference for streaming over traditional TV compared to the other clusters. Notably, they express the strongest desire for additional interactive features, indicating openness to experimentation and innovation despite a less exclusive reliance on streaming platforms.

5.6 Attitude towards on-screen products

This section analyzes the set of questions on attitude towards on-screen products using descriptive statistics and applies cluster analysis to identify high-level patterns in user behavior.

The results reported in Table 5 have relatively narrow confidence intervals across all variables, indicating high precision in the estimated means and a stable response distribution. They results suggest that product placement is relatively evident to viewers (*awareness of product placement* has a mean score of 3.73, with 59.6% of positive responses), and that is generally not perceived as particularly intrusive among respondents (*Annoyance with product placement* has a mean score of 2.19, with only 12.5% of the respondents reporting discomfort). Moreover, respondents tended to perceive it as less disruptive and more natural than traditional ads (*Product placement better than traditional ads* has a mean score of 3.52, with 56.7% of positive responses). The results also indicate a moderate level of perceived brand influence (mean score of 2.65, with only 22.1% of positive responses), and a relative low perceived impact on video quality (mean score of 2.95, with 34.6% of positive responses).

The cluster analysis produced three distinct clusters, and ANOVA results support the presence of meaningful differences between clusters (see, Table 6 for mean and standard deviation). In particular, four out of five variables show statistically significant differences between the identified clusters, indicating meaningful distinctions in user attitudes. The variable *PP awareness* did not show significant differences across clusters, suggesting that awareness of product placement is relatively uniform among all groups.

Based on the responses to the five questions, we label each cluster as follows:

- *PP Enthusiasts* (Cluster 0: 38 users). Users in this cluster report the most positive attitudes toward product placement. They show high awareness, low perceived annoyance, a strong preference for product placement over traditional advertising, and the highest agreement that product placement can improve content quality. Perceived influence on brand perception is also stronger in this group compared to the other clusters.
- *PP Indifferent* (Cluster 1: 25 users). Users in this cluster generally tolerate product placement. They report moderate awareness and very low annoyance levels, but relatively low perceived influence on brand perception. While they still tend to prefer product placement over traditional advertising, they show only moderate agreement that it improves content quality.

Table 5 Descriptive statistics for attitude towards on-screen products

Variable	Mean	Std.	% positive	95% CI	
				Dev. (≥ 4)	lower upper
PP awareness	3.73	1.01	59.6	3.53	3.93
PP annoyance	2.19	1.03	12.5	1.99	2.39
PP brand perception influence	2.65	1.00	22.1	2.46	2.85
PP better than traditional Ads	3.52	1.32	56.7	3.26	3.78
PP improves content quality	2.95	1.37	34.6	2.69	3.22

Table 6 Mean and standard deviation for each variable by cluster (scale 1–5)

Variable	Cluster 0	Cluster 1	Cluster 2
PP awareness	3.97 ± 0.88	3.60 ± 1.08	3.59 ± 1.05
PP annoyance	1.87 ± 0.88	1.36 ± 0.49	3.00 ± 0.84
PP Brand Perception Influence	3.47 ± 0.76	1.68 ± 0.56	2.49 ± 0.78
PP better than traditional ads	4.42 ± 0.64	4.08 ± 0.86	2.34 ± 1.13
PP improves content quality	3.84 ± 1.22	3.04 ± 1.21	2.07 ± 1.01

- *PP Sceptics* (Cluster 2: 41 users). Users in this cluster display a more critical attitude toward product placement. Although awareness levels remain moderate, they report the highest levels of perceived annoyance, the lowest preference for product placement over traditional advertising, and weak agreement that product placement improves content quality.

5.7 Past attitudes towards product placement

This section analyzes the set of questions on past attitudes towards product placement using descriptive statistics and applies cluster analysis to identify high-level patterns in user behavior.

The results reported in Table 7 have narrow confidence intervals and indicate moderate mean scores across all responses. *Enjoys searching online for products seen in video content* has a mean score of 2.64, with 24% positive responses. *Influence of Product Placement on Purchases* indicates that its perceived impact on purchasing decisions is low, with only 3.8% positive responses. However, 10.6% of respondents reported having purchased a product after seeing it in video, indicating that product placement can be associated with follow-up behaviors and warrants further empirical exploration.

The cluster analysis produced three distinct clusters, and the ANOVA results indicate that user groups exhibit distinct patterns of engagement with product placement (see, Table 8 for mean and standard deviation). All four dimensions

Table 7 Descriptive statistics for past attitudes towards product placement

Variable	Mean	Std. Dev.	% positive (≥ 4)	95% CI lower	95% CI upper
I searched for info after seeing PP	2.36	1.17	20.2	2.13	2.58
I purchased after seeing PP	1.88	0.97	10.6	1.69	2.06
I enjoy searching for PP products	2.64	1.24	24	2.40	2.88
PP influenced my purchases	2.00	0.86	3.8	1.83	2.17

Table 8 Mean and standard deviation for each variable by cluster (scale 1–5)

Variable	Cluster 0	Cluster 1	Cluster 2
I searched for info after seeing PP	1.58 ± 0.67	4.00 ± 0.71	2.85 ± 0.99
I purchased after seeing PP	1.50 ± 0.73	3.62 ± 0.65	1.79 ± 0.70
I enjoy searching for PP products	1.83 ± 0.81	3.62 ± 1.26	3.41 ± 0.97
PP influenced my purchase	1.60 ± 0.69	3.23 ± 0.83	2.13 ± 0.61

contributed to differentiating the identified clusters: the most pronounced differences are in *I searched for info after seeing PP* and *I purchased after seeing PP* (F-statistics of 58.4 and 46.9, respectively), suggesting that these two behaviors play an important role in differentiating user groups.

Based on the responses to the four questions, we label each cluster as follows:

- *PP Past Indifferent* (Cluster 0: 52 users). Users in this cluster report the lowest levels of engagement with product placement–related behaviors. They show minimal information-seeking activity after seeing products on screen, low enjoyment in searching for featured products, and very limited self-reported purchasing influenced by product placement.
- *PP Past Influenced* (Cluster 1: 13 users). Users in this cluster report the highest levels of engagement with product placement–related behaviors. They search for information about featured products, report the highest rates of purchases influenced by product placement, and show strong agreement that product placement has affected their purchasing decisions.
- *PP Past Curious* (Cluster 2: 39 users). Users in this cluster display moderate engagement with product placement–related behaviors. They report relatively high levels of information seeking and enjoyment in searching for featured products, but lower levels of actual purchasing influenced by product placement compared to

Table 9 Descriptive statistics for tool interest variables

Variable	Mean	Std. Dev.	% Positive	95% CI lower	95% CI upper
Tool usefulness	2.94	1.12	31.7	2.72	3.16
Willingness to use the tool	3.25	1.21	45.2	3.01	3.49
Interest in purchase suggestions	2.50	1.17	19.2	2.27	2.73
Interest in price comparison	2.62	1.32	25	2.36	2.87

Table 10 Mean and standard deviation for each variable by cluster (scale 1–5)

Variable	Cluster 0	Cluster 1	Cluster 2
Tool usefulness	3.59 ± 1.14	3.64 ± 0.72	2.09 ± 0.72
Willingness to use the tool	3.73 ± 0.77	2.17 ± 0.77	1.57 ± 0.69
Interest in purchase suggestions	4.14 ± 0.77	2.56 ± 0.77	1.67 ± 0.63
Interest in price comparison	4.09 ± 0.97	2.56 ± 1.13	1.96 ± 1.01

the most engaged cluster. This pattern suggests curiosity toward on-screen products that does not consistently translate into purchase behavior.

5.8 Interest in the proposed framework

This section analyzes the set of questions on user interest in the proposed interactive product placement framework using descriptive statistics and applies cluster analysis to identify high-level patterns in user behavior.

The results reported in Table 9 have narrow confidence intervals, indicating precision and reliability in the estimated means. Nearly half of the participants expressed a willingness to use the framework (*Willingness to use the tool* has a mean score of 3.25, with 45.2% of positive responses). A third of the participants perceive the tool as useful (*Tool usefulness* has a mean score of 2.94, with 31.7% positive responses). On-screen purchase suggestions generated the lowest levels of interest among respondents (*Interest in Purchase Suggestions* with has a mean score of 2.50 and only 19.2% positive responses).

The cluster analysis produced three distinct clusters, and the ANOVA results support the presence of significant differences between clusters, indicating clear segmentation in user interest toward the proposed framework (see, Table 10 for mean and standard deviation). The highest F-statistic value is observed in *Purchase suggestions* (72.8), suggesting that preferences regarding product suggestions play an important role in differentiating the identified clusters.

Based on the responses to the four questions, we label each cluster as follows:

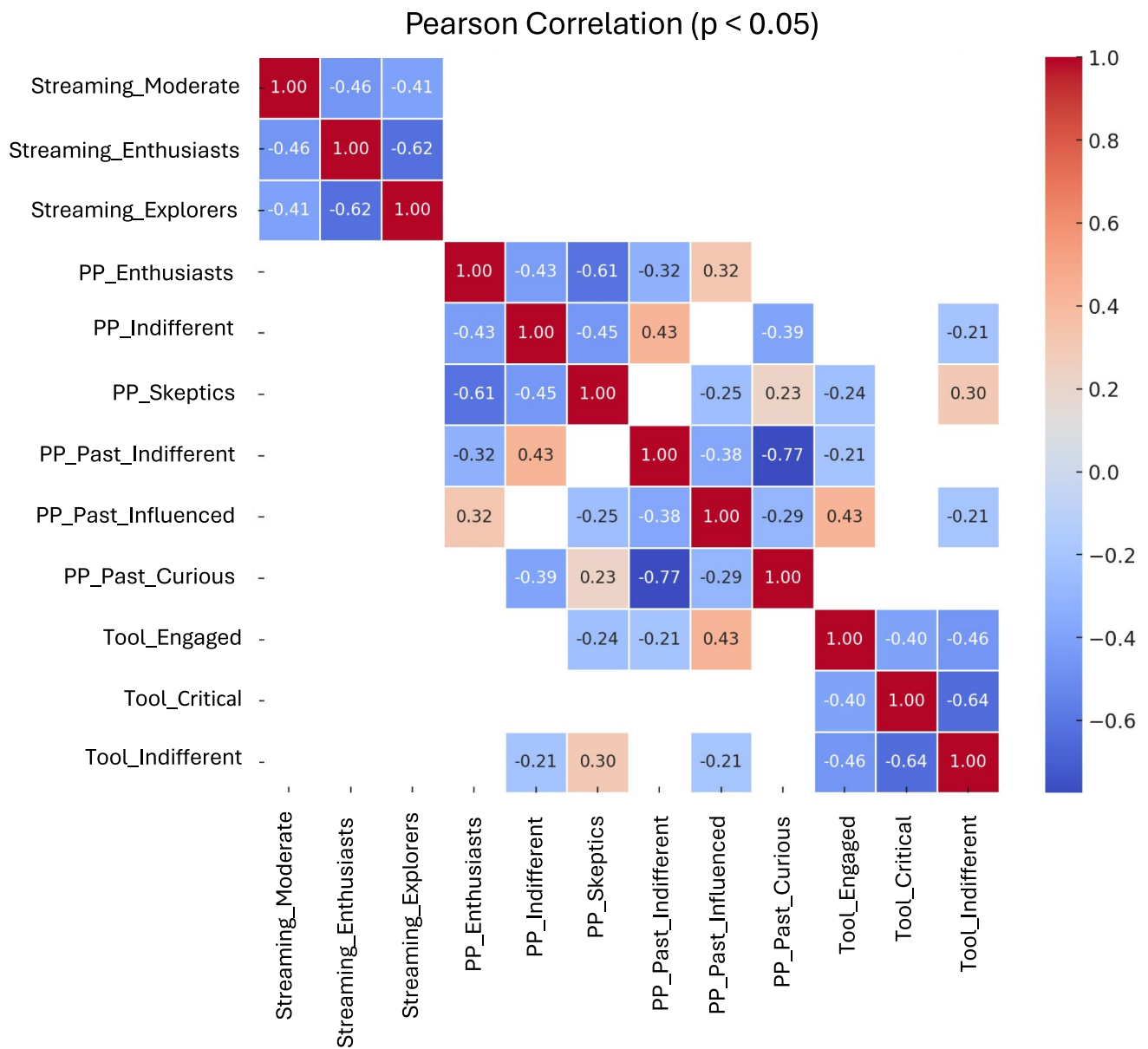


Fig. 6 Pearson correlation between clustering categories. Only statistically significant results ($p < 0.05$) are shown

- *Tool Engaged* (Cluster 0: 22 users). Users in this cluster show the strongest overall engagement with the proposed tool. They report high perceived usefulness, the highest willingness to use the system, and very strong interest in additional features such as purchase suggestions and price comparison.
- *Tool Indifferent* (Cluster 1: 36 users). Users in this cluster report the highest interest towards the proposed tool but also report intermediate levels of perceived usefulness and willingness to use the system, together with moderate interest in purchase suggestions and price comparison features.
- *Tool Critical* (Cluster 2: 46 users). Users in this cluster show weak engagement with the proposed tool. They

report low perceived usefulness, low willingness to use the system, and limited interest in additional features such as purchase suggestions and price comparison.

5.9 User behaviors

Understanding the relationships between user clusters can provide valuable insights for refining product placement strategies and tailoring tool adoption approaches. Correlation analysis enables us to identify key behavioral overlaps, helps to identify how specific user segments relate to both product placement and the proposed framework. Figure 6 summarizes the correlation analysis (only statistically significant results are reported).

Because each clustering framework defines mutually exclusive groups of users, negative correlations naturally emerge between clusters within the same category (e.g., 'PP Enthusiasts' vs. 'PP Skeptics'). These are expected by design and therefore less informative. The analysis instead focuses on relationships between clusters across categories, which reveal more meaningful behavioral patterns. Merging clusters into a single dimension would risk obscuring these contrasts and reducing interpretability. The analysis indicates a notable association between attitudinal dimensions and interest in the tool. In particular, 'PP Skeptics' and 'PP Past Influenced' exhibit the highest correlations with tool engagement, highlighting the importance of user attitudes in predicting interest in the proposed solution.

This analytic approach provides a more nuanced view of engagement dynamics. For example, a positive correlation (0.32) was observed between 'PP Enthusiast' and 'PP Past Influenced' users, suggesting that individuals who generally view product placement favorably are also more likely to have responded positively to such content in the past. Furthermore, the correlation (0.43) between 'PP Past Influenced' and 'Tool Engaged' users highlights this group's openness to innovative product placement solutions. Interestingly, a moderate correlation (0.30) was found between 'PP Skeptics' and 'Tool Indifferent' users, indicating that even individuals who are generally critical of product placement may still perceive value in the proposed framework. This suggests that the tool's interactive and user-driven approach may appeal beyond the traditionally receptive audience, expanding its potential adoption.

This type of analysis may have practical implications for both streaming platforms and advertising agencies. For example, in a potential application scenario, a brief questionnaire during the registration process could help classify new users into clusters, allowing platforms to explore ways of tailoring advertising experiences, such as offering more interactive options to engaged users or reducing ad frequency for more skeptical users. Similarly, advertisers could potentially use these insights to inform budget allocation and campaigns design, targeting specific user segments based on demonstrated openness to contextual and interactive advertising formats.

6 Discussion

The experimental evaluation suggested that users are interested in non-intrusive, personalized, and interactive advertising messages linked to on-screen products. This study offers contributions from theoretical, practical, economic, and sociocultural perspectives, while also acknowledging its limitations and outlining future directions.

6.1 Theoretical contribution

This study contributes to the theoretical understanding of product placement strategies in video streaming, particularly by addressing the issue of temporal relevance in digital content. Traditional product placement strategies, as established in the literature, fix the relevance of the product at the time of filming. However, the increasing availability of digital platforms and video contents requires an approach that extends this relevance over time. Our work builds on and extends existing theories of advertising by suggesting that this extended relevance can be achieved without relying on resource-intensive solutions, such as advanced graphics or augmented reality [11, 12]. By illustrating how computationally efficient solutions, such as JavaScript-based overlays, can maintain contextual relevance and enable dynamic interaction with viewers, our approach offers an alternative to traditional assumptions about the high computational costs typically associated with these interventions.

A second important issue concerns the intrusiveness of the proposal. Our approach aligns with and extends theoretical frameworks of non-invasive advertising strategies. In particular, the "pull" approach, as discussed in [27], suggests that advertising effectiveness increases when it aligns with user preferences and autonomy. Finally, our study strengthens and expands theories related to user engagement and advertising in digital environments. In particular, it contributes to recent research exploring the opportunity for impulse buying within video content [48–51].

6.2 Practical and economic contributions

From a practical perspective, the proof of concept illustrated the feasibility of using low-complexity technologies to connect video content with overlay messages. The findings provide preliminary insights that may inform marketers, advertisers, and media producers interested in delivering personalized advertising messages more efficiently.

From an economic perspective, the proposed framework could offer streaming platforms opportunities to diversify revenue streams without requiring significant computational resources. Advertisers might benefit from more efficient budget allocation by reaching audiences more likely to engage with their products. Because the framework does not alter the video content and is activated only upon viewer request, it may be compatible with premium subscription models that aim to avoid intrusive advertising. Additionally, by leveraging targeted contextual data, the approach has the potential to increase engagement and, consequently, the value of advertising inventory, though this requires further empirical validation. Finally, by lowering technological and financial barriers, the proposed system could make product

placement more accessible to smaller advertisers, potentially broadening the advertiser base. It is important to note that actual return on investment and engagement frequency must be validated in real-world deployments. Future work should include pilot studies and controlled experiments to gather quantitative evidence on engagement rates, incremental revenue, and cost–benefit ratios compared to traditional advertising approaches.

6.3 Sociological/cultural impact

The proposed framework is designed to give consumers greater autonomy over whether and when to view product placement messages. This aligns with broader cultural shifts toward more active and participatory forms of digital media consumption, in which users increasingly expect to control how they engage with content. This trend is consistent with the rise of participatory culture [52], where audiences are not merely passive recipients but active participants in content creation and interaction.

Culturally, the framework offers an alternative to traditional advertising by aiming to integrate promotional content more seamlessly into entertainment experiences. By personalizing advertising to reflect diverse audience preferences, it may support more authentic and culturally sensitive interactions. While the framework aspires to foster less intrusive marketing practices, its actual impact on cultural engagement patterns should be examined through longitudinal and cross-cultural studies.

6.4 Limitations and future directions

As an initial exploratory study, our aim was to establish a conceptual and technical foundation for interactive product placement rather than to provide exhaustive empirical validation. Within this scope, several limitations should be acknowledged to contextualize the findings and to guide future research.

6.4.1 Limitations

First, the evaluation relied on self-reported questionnaire data rather than behavioral measures collected in real-world settings. While this approach provides valuable initial insights into user perceptions, it does not capture actual interaction patterns, sustained behaviors, or engagement in naturalistic contexts.

Second, the study sample consisted of 104 young adults from a specific demographic group. This focus enabled the investigation of a relevant and advertising-sensitive population; however, it limits the generalizability of the findings

to broader audiences that may differ in cultural background, age, or socioeconomic characteristics.

Third, the experimental context involved a proof-of-concept environment rather than integration into operational streaming platforms. Although this controlled setting was useful for isolating the effects of the proposed framework, it may not fully reflect the complexity of real-world streaming scenarios, where factors such as technological constraints, competing stimuli, and varied viewing contexts can influence outcomes.

Fourth, some item groupings were intentionally designed as multidimensional, formative constructs for exploratory purposes. While this choice may limit direct comparability with studies relying on validated unidimensional scales, it enabled a broader and more nuanced assessment of user behaviors and attitudes at this early stage of investigation.

Finally, the study design did not include longitudinal measurements. As a result, it does not provide evidence about long-term user engagement, habituation effects, or potential changes in attitudes and behaviors over time [53].

6.4.2 Future directions

These limitations open up several opportunities for future research. Expanding the demographic diversity of participants would strengthen the external validity of the findings. Integrating behavioral data (e.g., click-through rates, interaction logs) and advanced user interaction techniques (e.g., eye-tracking, biometric feedback) could offer more fine-grained insights into attention and engagement mechanisms.

Future work should also refine the measurement instruments by developing validated unidimensional scales for specific constructs, while preserving the multidimensional insights identified in this exploratory phase.

Collaborations with streaming platforms represent a particularly promising direction, enabling large-scale field studies and longitudinal analyses to evaluate real-world effectiveness, economic impact, and adoption dynamics over time. Additionally, investigating personalization strategies, such as timing, tone, and level of customization, could help refine user experience and enhance advertising effectiveness in diverse contexts [7, 22].

In summary, while the study's scope is intentionally limited, it provides a foundational step toward rethinking product placement as an interactive, user-driven experience. By clearly identifying both the potential and the challenges of this approach, the work lays the groundwork for future empirical validation and large-scale implementation.

7 Conclusions

This study presented a prototype of a multimedia framework designed to explore a shift in video advertising from intrusive interruptions toward a user-activated product placement model. The approach enables viewers to access product information on demand through overlay boxes, which may enhance interactivity, personalization, and adaptability. From a technical perspective, the prototype demonstrated the feasibility of a lightweight client-based implementation that aims to reduce server load and to move product placement from filming time to playing time. A proof of concept and a questionnaire administered to 104 young adults indicated a preference for the proposed product placement model over traditional ads (56.7%) and a willingness to use the system among 45.2% of participants, including some initially skeptical respondents. These findings are encouraging but should be interpreted with caution. The study is limited by its relatively small and demographically narrow sample, reliance on self-reported perceptions rather than behavioral measures, and the lack of testing in real-world streaming environments. In addition, the evaluation was short-term and did not examine sustained user engagement or economic impacts. Future research should replicate the study with larger and more diverse populations, incorporate behavioral and longitudinal data, and evaluate the framework in operational streaming platforms to assess its effectiveness and adoption in real-world contexts.

Author contributions Marco Furini had the idea and wrote the manuscript.

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Data availability The data that support the findings of this study are available from the author upon reasonable request.

Declarations

Conflict of interest The authors declare no Conflict of interest.

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